

CSE 2017 Data Structures and Lab

Lecture #12: Graph 2

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Shortest-path problem

- There might be multiple paths from a source vertex to a destination vertex
- ***Shortest path***: the path whose total weight (i.e., sum of edge weights) is minimum

Austin→Houston→Atlanta→Washington:
1560 miles

Austin→Dallas→Denver→Atlanta→Washington:
2980 miles

Variants of Shortest Path

- **Single-pair shortest path**
 - Find a shortest path from u to v for given vertices u and v
- **Single-source shortest paths**
 - $G = (V, E) \Rightarrow$ find a shortest path from a given source vertex s to each vertex $v \in V$

Variants of Shortest Paths (cont'd)

- **Single-destination shortest paths**

- Find a shortest path to a given destination vertex t from each vertex v
- Reversing the direction of each edge \rightarrow single-source

- **All-pairs shortest paths**

- Find a shortest path from u to v for every pair of vertices u and v

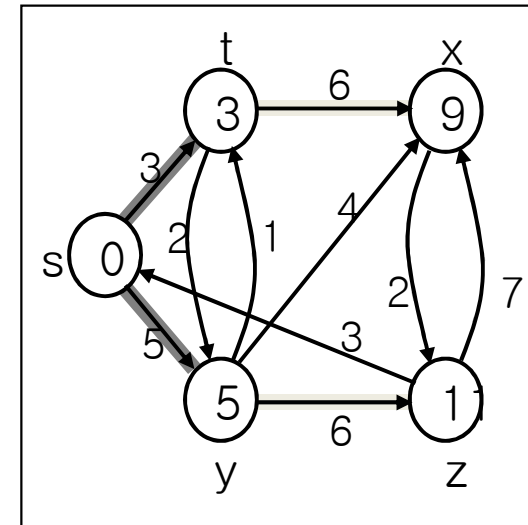
Notation

- **Weight of path** $p = \langle v_0, v_1, \dots, v_k \rangle$

$$w(p) = \sum_{i=1}^k w(v_{i-1}, v_i)$$

- **Shortest-path weight** from s to v :

$$\delta(v) = \begin{cases} \min_p w(p) : s \xrightarrow{p} v & \text{if there exists a path from } s \text{ to } v \\ \infty & \text{otherwise} \end{cases}$$



Shortest-path algorithms

- Solving the shortest path problem in a brute-force manner requires enumerating all possible paths.
 - There are $O(V!)$ paths between a pair of vertices in a acyclic graph containing V nodes.
- There are two algorithms
 - Dijkstra's algorithm
 - Bellman-Ford's algorithm(negative weights)

Shortest-path algorithms (cont'd)

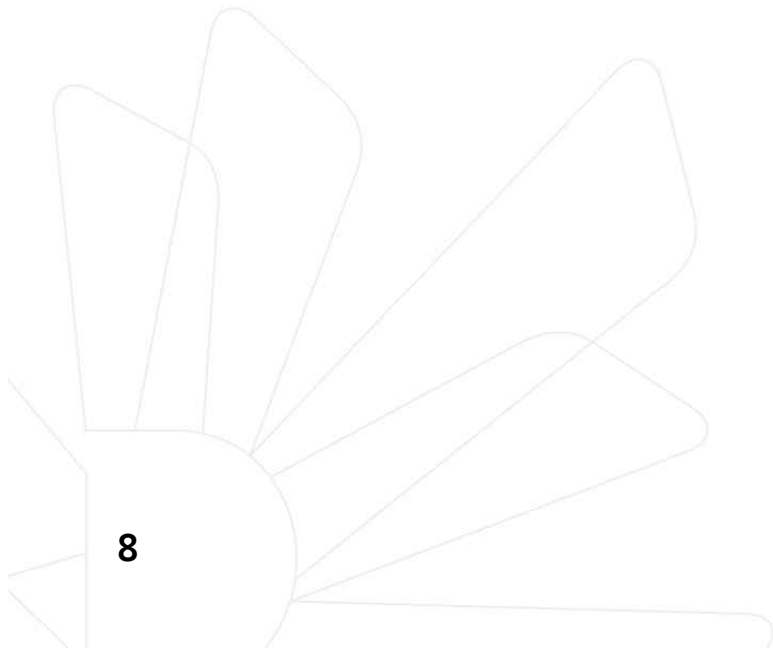
- Dijkstra's algorithm is "greedy" algorithms!
 - Find a "globally" optimal solution by making "locally" optimum decisions.
- Both Dijkstra's algorithm is iterative:
 - Start with a shortest path estimate for every vertex:
 $d[v]$
 - Estimates are updated iteratively until convergence:
 $d[v] \rightarrow \delta(v)$

Shortest-path algorithms (cont'd)

- **Two common steps:**

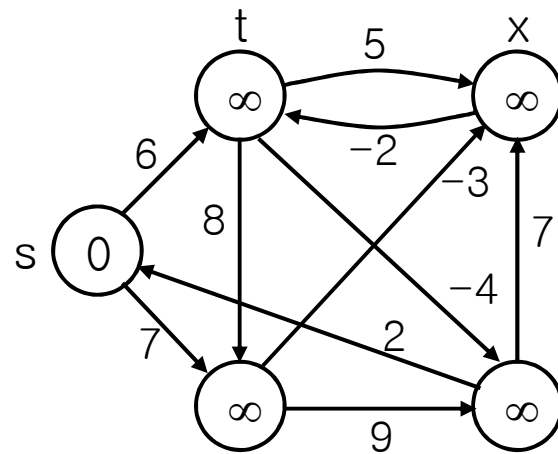
(1) Initialization

(2) Relaxation (i.e., update step)



Initialization Step

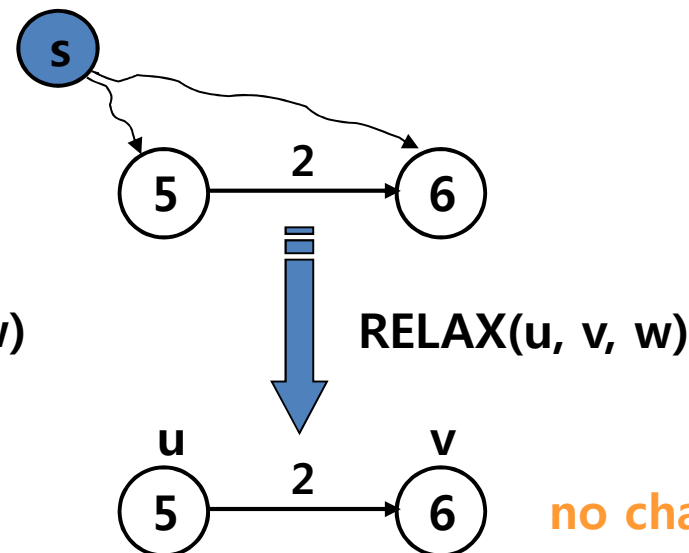
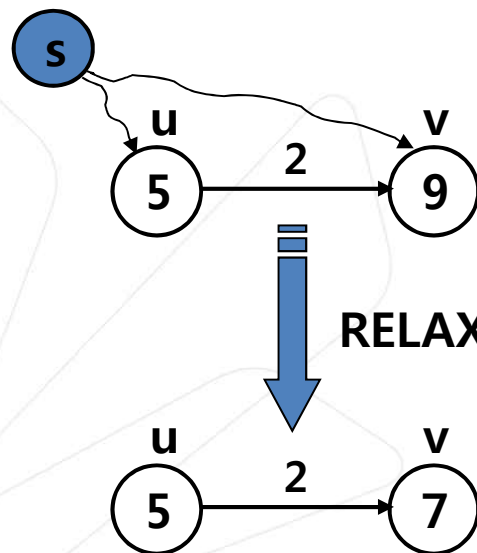
- Set $d[s]=0$ (i.e., source vertex)
- Set $d[v]=\infty$ (i.e., large value) for $v \neq s$



Relaxation Step

- Relaxing an edge (u, v) implies testing whether we can improve the shortest path to v found so far by going through u :

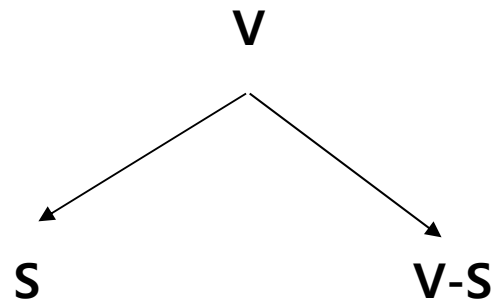
If $d[v] > d[u] + w(u, v)$
we can improve the shortest path to v
 $\Rightarrow d[v] = d[u] + w(u, v)$



no change

Dijkstra's Algorithm (cont'd)

- At each iteration, it maintains two sets of vertices:



$$d[v] = \delta(v)$$

(estimates **have converged** to the shortest path solution)

$$d[v] > \delta(v)$$

(estimates **have not converged** yet)

Initially, S is empty

Dijkstra's Algorithm (cont.)

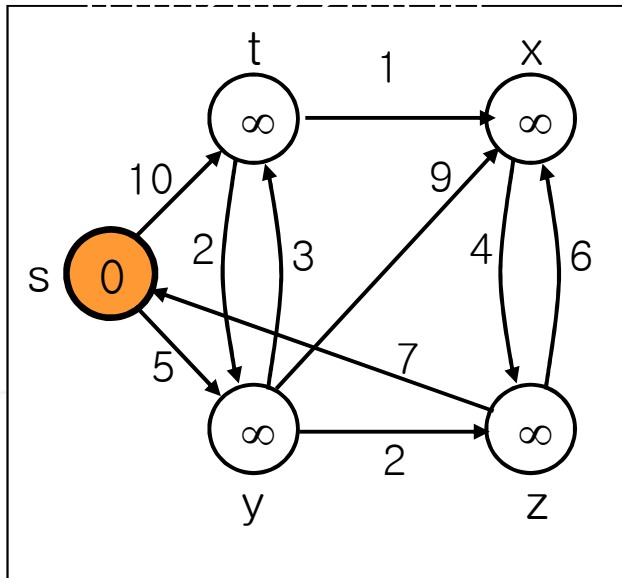
- Vertices in $V-S$ reside in a **min-priority queue** Q
 - Priority of u determined by $d[u]$
 - The “highest” priority vertex will be the one having the smallest $d[u]$ value.

Steps

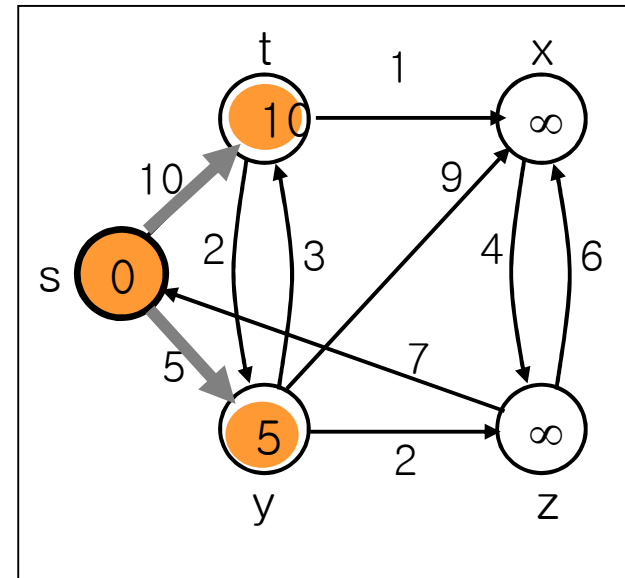
- 1) Extract a vertex u from Q
- 2) Insert u to S
- 3) Relax all edges leaving u
- 4) Update Q

Dijkstra (G, w, s)

$S = \langle \rangle$ $Q = \langle s, t, x, z, y \rangle$

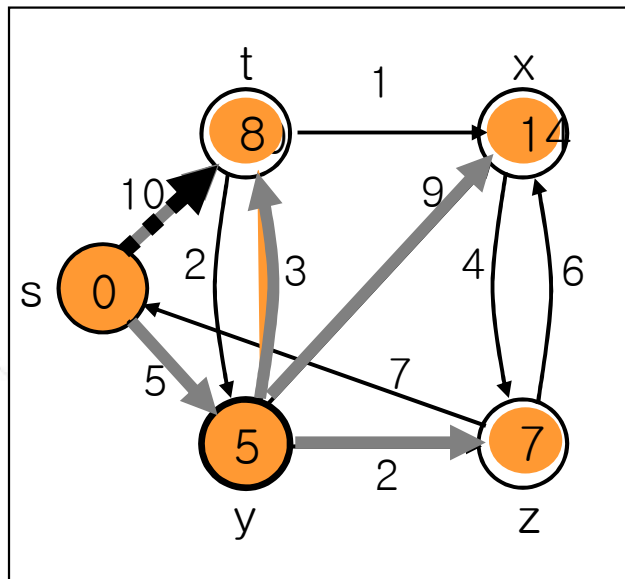


$S = \langle s \rangle$ $Q = \langle y, t, x, z \rangle$

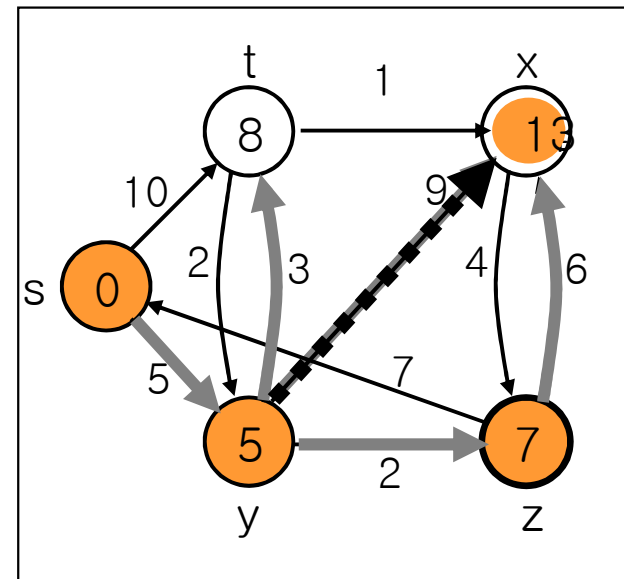


Example (cont.)

$S = \langle s, y \rangle$ $Q = \langle z, t, x \rangle$

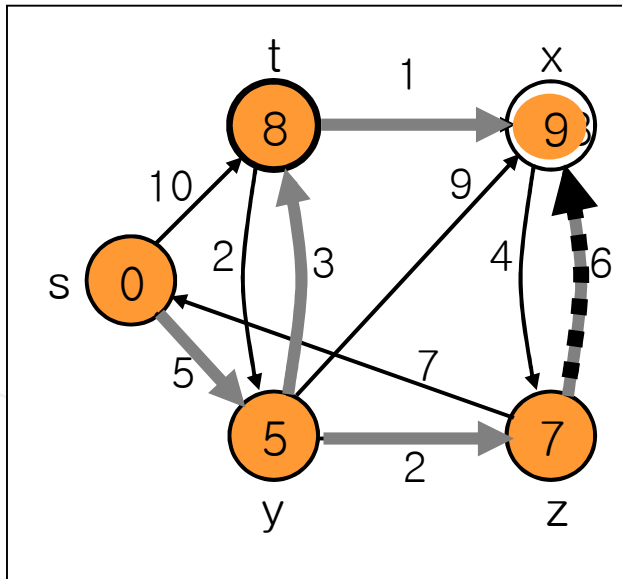


$S = \langle s, y, z \rangle$ $Q = \langle t, x \rangle$

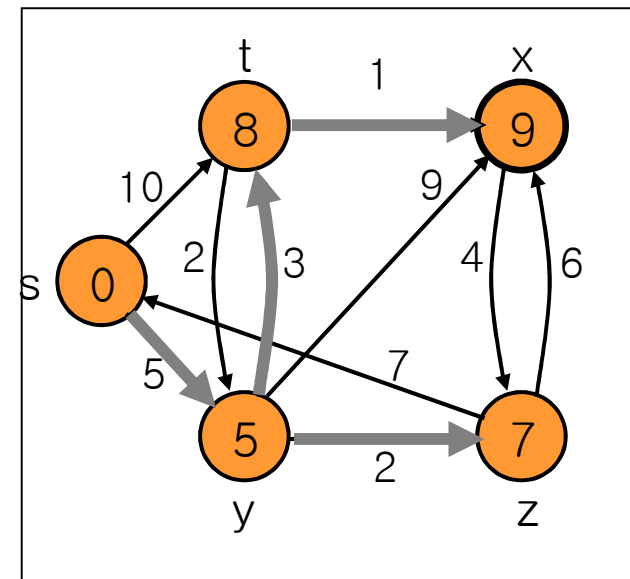


Example (cont.)

$S = \langle s, y, z, t \rangle$ $Q = \langle x \rangle$



$S = \langle s, y, z, t, x \rangle$ $Q = \langle \rangle$



Note: use back-pointers to recover the shortest path solutions

Dijkstra (G, w, s)

INITIALIZE-SINGLE-SOURCE(V, s) $\leftarrow O(V)$

S $\leftarrow \emptyset$

Q $\leftarrow V[G]$ build priority heap
 $\leftarrow O(V \log V)$ – but $O(V)$ is a tighter bound

while Q $\neq \emptyset$ $\leftarrow O(V)$ times

do u \leftarrow EXTRACT-MIN(Q)

S $\leftarrow S \cup \{u\}$ $\leftarrow O(\log V)$

for each vertex v \in Adj[u] $\leftarrow O(E_{v_i})$

do RELAX(u, v, w)

Update Q (DECREASE_KEY) $\leftarrow O(\log V)$

} $O(E_{v_i} \log V)$

Overall: $O(V + 2V \log V + (E_{v_1} + E_{v_2} + \dots) \log V) = O(V \log V + E \log V) = O(E \log V)$